$ifclassloadedbeamer$

Next Token Generation

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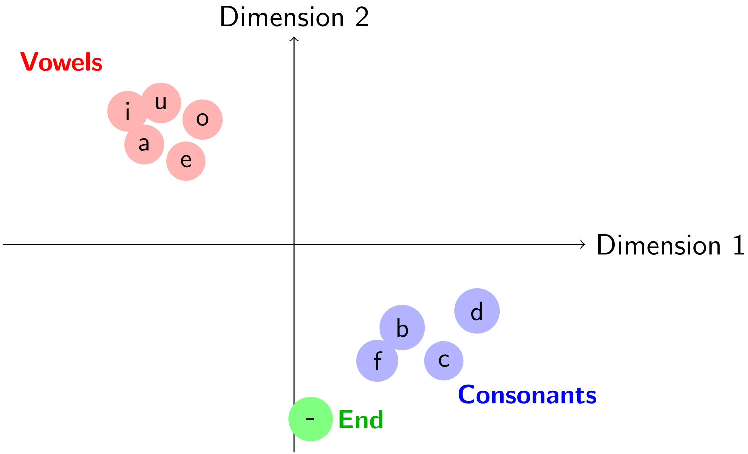
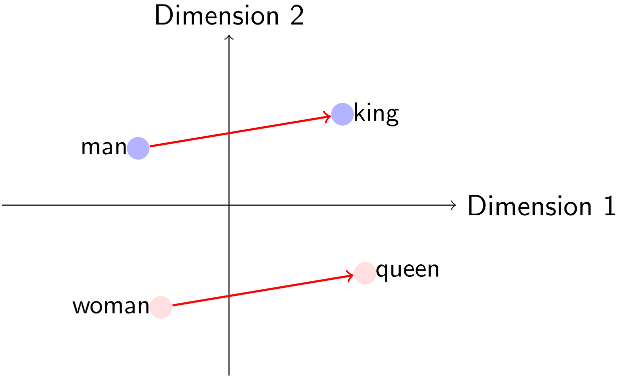
Vocabulary Size:

26 letters $+$ 1 hyphen $=$ **27 characters**


Dimension 2
Vowels
i
u
o
a
e
Dimension 1
d
b
f
c
Consonants
-
End

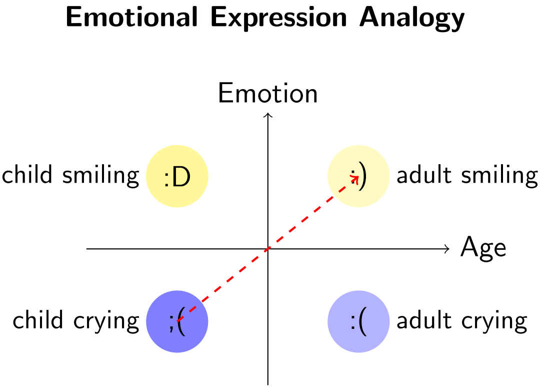
Word2Vec Analogy Example

Classic Word2Vec Relationship



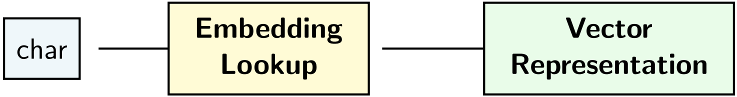
Relationship: queen ≈ king - man + woman

Analogy with Emotions



Relationship: child crying = child smiling + adult crying - adult smiling

Embedding Matrix/Table Concept



Process: Character → Lookup in Embedding Table → Dense Vector

Embedding Table Structure

27 × K Embedding Matrix

Char	D1	D2	...	DK
a	0.2	-0.1	...	0.8
b	-0.3	0.5	...	-0.2
c	0.1	0.3	...	0.4
⋮	⋮	⋮	⋱	⋮
z	0.7	-0.4	...	0.1
-	0.0	0.9	...	-0.5

Key Point

Each character maps to a K-dimensional vector.

Learnable Parameters

- **Embedding Matrix:** 27 $\times$ K parameters
  - Initially random

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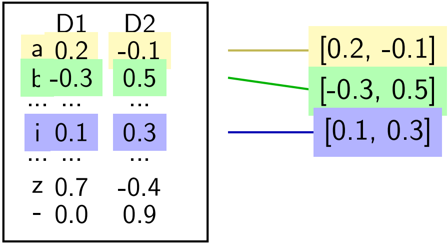
- **Embedding Matrix:** 27 × K parameters
  - Initially random
  - Updated during training via backpropagation
  - Learns meaningful character representations
- **Neural Network Weights:** MLP parameters
  - Transform concatenated embeddings to output
  - Learn classification patterns
- **Total Learnable Parameters:**
  - Embedding: 27 × K
  - MLP: (context_size × K) → hidden → ... → 27

Example: 2D Embeddings for “abi”

Embedding Matrix (27 × 2)

Input: X = [“a”, “b”, “i”]



	D1	D2
a	0.2	-0.1
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…	…	…
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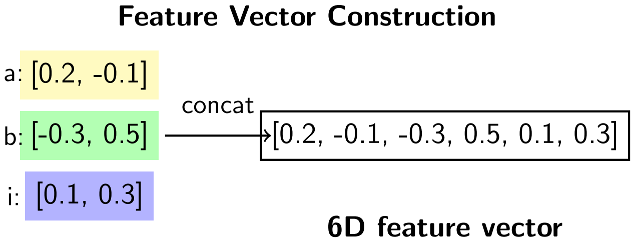
[0.2, -0.1]

[-0.3, 0.5]

[0.1, 0.3]

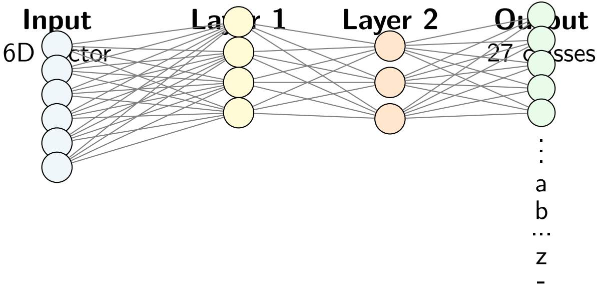
Concatenate the Embeddings



Result

3 chars × 2D embeddings = 6D input to neural network

Multi-Layer Perceptron Architecture



Training Objective

- **Loss Function:** Cross-entropy loss for multi-class classification

$$\mathcal{L} = -\sum_{i=1}^{N} \sum_{c=1}^{27} y_{i,c} \log(\hat{y}_{i,c}) \tag{1}$$

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  3. Backward pass: Update both embeddings and MLP weights
  4. Repeat for all training examples

Sampling from the Learned Model

Test Input: “abi”

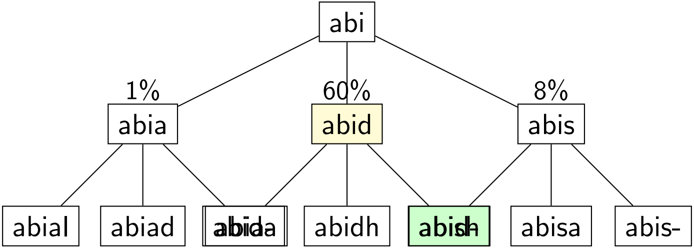
Predicted Probability Distribution

Next Char	**Probability**	**Next Char**	**Probability**
a	0.01	n	0.05
b	0.01	o	0.02
c	0.03	p	0.01
d	**0.60**	q	0.00
e	0.02	r	0.03
f	0.01	s	0.08
…	…	…	…
-	0.05	z	0.01

Most Likely Continuation

“abi” → “abid” (60

Generation Tree Structure



Complete name: “abid”

Recursive Process: Sample next character, append, repeat until end token

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- **Standard Softmax:**

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{27} e^{z_j}} \tag{2}$$

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  - $T \to 0$: More peaked (deterministic)
  - $T \to \infty$: More uniform (random)

Temperature Variations

Context: “abi” → Next character probabilities

Char	**T=0.5 (Low)**	**T=1.0 (Default)**	**T=2.0 (High)**
a	0.001	0.01	0.08
d	**0.95**	**0.60**	**0.25**
s	0.01	0.08	0.12
h	0.005	0.03	0.09
-	0.02	0.05	0.11
others	0.015	0.23	0.35

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- **Low T:** Conservative, predictable
- **High T:** Creative, diverse

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- **Applications:** Foundation for modern language models
    - GPT models use the same principle
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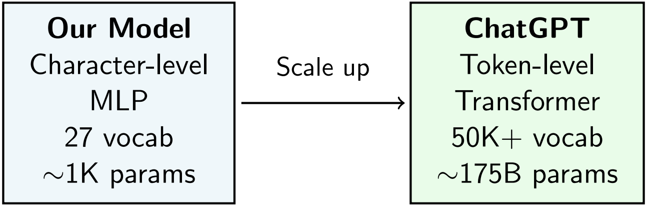
    - Transformer architecture instead of MLP
    - Billions of parameters instead of thousands

From Character-Level to ChatGPT



Our Model
Character-level
MLP
27 vocab
~1K params

Scale up

ChatGPT
Token-level
Transformer
50K+ vocab
~175B params

Same fundamental principle: Predict the next token!